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A Risk Comparison between Traditional and Responsible Investing using CAViaR

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Abstract

As the most used risk measure, Value at Risk allows for the expression of the market risk associated with any portfolio through one monetary number. This paper employs a new VaR approach, the Conditional Autoregressive Value at Risk, which specifies the evolution of quantiles over time using an autoregressive methodology and it estimates the parameters with quantile regression. The model is used to investigate whether sustainable financial instruments are able to reduce risk exposure. For that purpose an index comparison between a sustainable and a traditional instrument has been performed.

Keywords: CAViaR, ESG investing, Risk Management, Responsible Investing

1 Introduction

Over the last decades, the interest in social and environmental issues has put the subject on a trending line. There is evidence that natural resources will not be the main drivers of growth in the long term, as indicated by Paul Romer and William Nordhaus (2018 Economics' Nobel Prize). Yearly measures, such as the Earth Overshoot Day[1], are empirical proof that humanity's demand for ecological resources and services exceeds what the earth can regenerate in a year. The overconsumption of resources is expected to see the growth of regulations and restrictions to bring future prosperity. Instead, the boundaries of future economic growth will be enlarged by technology and know-how.

Consequently, the new generation, called Millennials, is becoming more sensitive to the topic: they prefer to direct their investments towards companies with high environmental, social and governance (ESG) ratings, expressed through the advertising of conscious and transparent business ethics. The definition given by MSCI, an ESG Data Provider that is a leader in its sector and has been operating in the field since 2007, of ESG Rating is: "*The ESG Rating is designed to measure a company's resilience to long-term , industry material environmental, social, and governance risks*". A 2019 Morgan Stanley Institute for Sustainable Investing survey indicated that 95% of millennials were interested in sustainable investing. It reflects a new society's desire to align the return of their investment with their values. Moreover, this research illustrated that investors are increasing the number of questions to their wealth managers, and they take into consideration how their invested money impacts society and the planet at large.

The financial industry has been following the same path: the ESG movement began

[1] https://www.overshootday.org/

taking shape across different industries nearly 30 years ago. In the beginning, it simply was an add-on practice, done by large public companies, to implement socially responsible initiatives (SRI). In financial terms, ESG defined how investors evaluated companies' impact on broader society. The primary purpose remains true; however, ESG has evolved from a supplementary practice into an ethos, supporting market participants in their investment decisions, providing them with ESG-data, which can accompany financial data, offering a complete view of the company. ESG-data allows one to look below the surface of a company to get a long-term perspective. Instead of looking only at revenues, dividends, profitability, ESG data providers integrate the vision with extra information such as energy efficiency, litigation risks, corruption indexes, and staff turnover. A study by Global Sustainable Investment Alliance reports that, as of 2018, European socially responsible investments (SRI) that refer to an investment approach in which ESG factors are integrated into the research, analysis, and selection process of the portfolio management, accounted for 48.8% of the total assets managed in Europe (see Figure 9 in the Appendix for more information). Globally, SRIs assets under management amounted to $30.7 trillion (see Figure 10 in the Appendix for more information). The second fundamental definition of SRI is sustainable and responsible investment. Eurosif, the leading European SRI membership organization whose mission is to promote sustainability through European financial markets, defines it as "*a long-term oriented investment approach which integrates ESG factors in the research, analysis and selection process of securities within an investment portfolio. It combines fundamental analysis and engagement with an evaluation of ESG factors in order to better capture long-term returns for investors, and to benefit society for influencing the behavior of companies*" (European SRI Study 2016, 9).

On the other hand, a focus on ESG can help a company understand the positive impact and manage risks its operations have on customers, investors, employees, and communities. It is a more implemented way of assessing a company's success, going beyond its balance sheet, and looking at how it impacts the broader society.

According to Clark, Feiner, and Viehs (2015), an interesting factor that differentiates responsible investing from traditional investing is that increasing ESG standards of a company leads to improved performance and reputation and a decrease in risk. This last statement has been empirically demonstrated by Kumar, Smith, Badis, Wang, Ambrosy, and Tavares (2016). A recent empirical example of poor risk management that has negatively impacted its reputation and financial performance is Wirecard. The company is a German payment processor and financial services provider, operating worldwide, with more than 7,000 clients. In the early months of 2019, two Financial Times journalists hypothesized alleged accounting irregularities in the Singapore Wirecard division, which were harshly criticized by Bafin[2], Germany's top financial overseer. A few months later, in June 2020, Wirecard filed for insolvency after revelations that €1.9 billion were missing, and the termination and arrest of its CEO Markus Braun. The following days, share prices collapsed from €100 to €2 in less than a week (see Figure 11 in the Appendix). According to MSCI Risk Management indicators, from its Software & Services Industry report, Wirecard violated transparency and reliability of reported financials and audit oversight.

As empirically shown by the Wirecard example, inadequate risk management control can lead to a riskier stock. When evaluating a company, MSCI considers its exposure to

[2] Federal Financial Supervisory Authority in Germany

risk and its risk management quality, analyzed through ESG rating methodologies. However, focusing on the financial instrument's exposure, according to Broadstock, Chan, Cheng, Wang (2020), there is evidence that a higher ESG rating exhibits lower price volatility, especially during the COVID-19 period. The more a financial instrument is "ESG" compliant, the less exposure to extreme events they have.

According to MSCI, more-in-depth and more consolidated analysis regarding the risk exposure and risk management analysis brings a strong track record of performance in managing its specific risks or opportunities. An example is the MSCI ESG Ratings methodology: the data provider computes each company's exposure to crucial ESG risks based on a company's business granular breakdown. If the company has ongoing or structural controversies[3] that occurred within the last three years, it will impact the overall management score on each ESG aspect in which it is involved.

The present study's central point is the Conditional Autoregressive Value at Risk (CAViaR) risk analysis on two indexes, one sustainable and one traditional, to measure each instrument's riskiness, as measured by the fatness of tails. The emphasis on the model's impacted risk value can show if the sustainable index is less risky. The CAViaR model provides evidence that a risk exposure reduction is implied across different sectors and indexes. However, the model has some difficulties when analyzing a situation of market stress, such as the Global Financial Crisis, because it is not able to capture exogenous and spillover effects.

The content of this Work Project is organized as follows: section 2 expands upon

[3] A controvere case is defined as an instance or ongoing situation in which a company's operations and/or products allegedly have a negative environmental, social and/or governance impact. MSCI ESG Rating Methodology, April 2020

essentials theoretical concepts underlying the current study and discusses the overall CAViaR risk methodology that will be used in the analysis; section 3 includes statistic outputs and results. It will contain the model outcomes which will be used to identify and assess risk in both of the analyzed indexes: the MSCI World ESG Leaders Index (GSIN) and the Standard & Poor 500 Index (SPX). It will also provide a comparison of ten pairs of stocks. Each pair will contain a constituent of GSIN and SPX, respectively, since the analysis is focused on demonstrating that ESG financial products are less risky than traditional investment products. Finally, section 4 summarizes the key points and provides concluding remarks.

2 Literature Review and Methodology

The standard measure of market risk is the Value at Risk (VaR), which is commonly used by financial practitioners due to its conceptual simplicity. VaR allows for the characterisation of the market risk associated with any portfolio through a monetary value, summarizing the need of different users and, consequently, finding a compromise. In spite of its conceptual simplicity, the measurement of risk is an interesting statistical problem. Artzner et al. (1997, 1999) have derived a set of axioms which provide the main statistical characteristics for coherent risk measurement. First, the maximum loss, measured by Value at Risk, that a portfolio can reach should not be exceeded. Second, the proposed risk measure should be greater than the mean loss that implies capital adequacy to cover losses. Third, if there is a proportional change in the loss, the risk measure must change proportionally. Lastly, the risk measure must satisfy the property of subadditivity, implying that the risk measure computed for two separate losses should be higher or equal to the risk measure computed on the two portfolios' sum.

The VaR is generally classified into two broad categories: the indirect-VaR approach and the direct-VaR approach. The first category includes the classical parametric, nonparametric, and semiparametric approaches. All three methodologies follow a standard structure, briefly summarized in three steps (Huang, Yu, Lu, Fabozzi, Focardi, Fukushima, 2010): 1) mark to market daily portfolio data; 2) the estimated portfolio's distribution and 3) a computed portfolio's VaR. The most challenging step is the second one since financial returns usually exhibit a few common features, demonstrated more than 50 years ago by Mandelbrot (1963) and Fama (1965): volatility clustering (high autocorrelation), significant kurtosis (peaked and fat-tailed), marginal skewness (time-varying nature) and autocorrelation of returns, in the case of an index. Consequently, following the indirect approach of computing VaR based on the inverse distribution function of returns is highly criticized by academic researchers and practitioners. Due to its conceptual intuition, VaR reduces the risk associated with assets to just a number that regulators, investors, and board members can effortlessly understand. Moreover, most VaR predictive models assume that time series follow a specific stochastic process, and the model is entirely determined by its parameters. However, parameters are estimated from data, often prone to structural changes due to regime shifts or critical events. This characteristic calls for the use of the second broad category, the direct-VaR models, since it does not require any assumption about the distribution of returns.

The direct-VaR category is a dynamic quantile regression approach. The methodology computes the quantile directly using regression techniques, not requiring any assumption regarding the returns' distribution. The CAViaR approach has been proposed and implemented by Engle and Manganelli (2004), and provides direct quantile estimation. CAViaR aims to take advantage of the empirical fact that stock market's volatilities cluster over time. Therefore, VaR, which is positively linked to the standard deviation, must exhibit similar behavior. Engle and Manganelli simulated 1,000 samples of 2,000 observations for seven different processes. They demonstrated that CAViaR outperforms most indirect-VaR methods when tearing into fat-tailed data. The methodology's strength is that it does not require any assumption about the return's distribution. An additional empirical study, performed by Kouretas and Zarangas (2005), used the CAViaR model to measure the market risk of five different equity markets, such as the New York Stock Exchange (NYSE) and the Athens Exchange. Through the analysis, they confirmed some stylized facts of financial data, such as volatility clustering.

Another useful broad classification are factor and portfolio models. The first category considers that the universe of assets is projected onto a limited number of factors whose volatilities and correlations have been forecasted. Consequently, the portfolio's risk variation depends on a time variation in the estimated factors' volatility or correlation. Moreover, the VaR is assumed to be proportional to the computed standard deviation of the portfolio, often assuming normality. Thus, the second category constructs historical returns that mimic the past performance of the current portfolio. VaR is computed based on a statistical model. The riskiness of this methodology is that changes are associated with the historical experience of the portfolio.

Regarding portfolio models, it becomes interesting to forecast the quantiles instead of historical returns once again. Several different approaches have been used; the first is the estimation of portfolio volatility by a generalized autoregressive conditional heteroscedastic (GARCH) model or exponential smoothing. The second step is the computation of VaR, always assuming normality. The model has been criticized because it assumes that negative tails follow the same pattern as the rest of the returns and that the distribution of the returns divided by its standard deviation will be iid, if not normal. Another method is to use rolling historical quantiles, assuming that any return in a specific period is equally likely. The critic that can be run in this second case is that the model assumes that for a specific window, such as a year, any return is equally likely, but a return older than a year has no probability of occurring. It implicitly implies that the return distribution does not vary over time, at least within a year.

2.1 The GARCH Model

The GARCH model was introduced by Bollerslev (1986). The methodology assumes that future variance has predictable behavior and that it is a function of the previous day variance (σ_{t-1}^2) and its innovation (R_{t-1}^2) weighted by their respective factor contributions (α and β). An example of a GARCH model is:

$$\sigma_{t|t-1}^2 = \lambda + \alpha R_{t-1}^2 + \beta \sigma_{t-1}^2$$

with $\lambda > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$.

2.2 The CAViaR Model

Conceptually, VaR is the potential expected loss over a certain period with a given confidence level. For a given significance level θ, let $\{y_t\}^T_{t=1}$ be a financial return series associated with a single financial instrument, conditional on the information set F_{t-1}. Then, VaR at time *t* is defined as the negative θ-quantile, $q_t(\theta)$, i.e.,

$$\Pr(y_t \leq -q_t(\theta) \mid F_{t-1}) = \theta. \qquad (1)$$

The VaR prediction is set at θ = 1% and 5%, which yield one-sided 99% and 95% VaRs. It is the typical VaR forecast used by banks (Berkowitz and O'Brien, 2002). Typically, using (1), a VaR prediction implies the specification of $F_t(\cdot)$. Once the dependence structure of $\{y_t\}$ can be fully described by a certain distribution function $F_t(\cdot)$, then VaR can be easily calculated. To reduce the difficulties in computing VaR, Engle and Manganelli (2004) proposed the CAViaR, this approach is based on the fact that financial volatility returns are highly autocorrelated (clustering). The main methodological advantage is that it does not require any return distribution assumption. Estimated inputs are a vector of portfolio returns, $\{y_t\}_{t=1}^{T}$. As considered before, let θ be the probability associated with VaR, let x_t be a vector of known parameters at time t, and let β_θ be a p-vector of unknown parameters. Lastly, let $f_t(\beta) \equiv f_t(x_{t-1}, \beta_\theta)$ be the time t θ-quantile of the distribution of portfolio returns formed at time t-1. A generic CAViaR specification is:

$$f_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_i f_{t-1}(\beta) + \sum_{j=1}^{r} \gamma_j l(x_{t-j}), \tag{2}$$

where p = q + r + 1 is the dimension of β and l(.) is a function of a finite number of lagged values. The autoregressive term ensures that the quantile changes smoothly over time. The l(.) function's role is to link $f_t(\beta)$ to observable variables that belong to the information set. The term has the same role as the news impact curve for GARCH models. Since a natural choice for x_{t-1}, are lagged returns, it is expected that the VaR increases as y_{t-1} becomes very negative because one bad day negatively influences the profitability of the next one. On the opposite, good days positively influence VaR for the next few days. Hence, VaR might symmetrically depend on $|y_{t-1}|$. Some examples of processes that will be used in the estimation process are:

Symmetric Absolute Value CAViaR (SAV):

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 |y_{t-1}| \tag{3}$$

Asymmetric Slope CAViaR (AS):

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3(y_{t-1})^+ + \beta_4(y_{t-1})^- \quad (4)$$

Indirect GARCH CAViaR:

$$f_t(\beta) = (\beta_1 + \beta_2 f^2_{t-1}(\beta) + \beta_3 y^2_{t-1})^{1/2}. \quad (5)$$

The symmetric and indirect GARCH models respond symmetrically to past returns, while the asymmetric one responds differently to positive and negative returns. The common characteristic is that they are all mean-reverting, in the sense that the coefficient on the lagged VaR is not constrained to be 1. Moreover, the symmetric and asymmetric models generalize the traditional GARCH-based VaR models by allowing for different stochastic processes in the tail of financial returns, and they can deal with non-iid processes. Lastly, the adaptive model has the following format:

Adaptive CAViaR:

$$f_t(\beta_1) = f_{t-1}(\beta_1) + \beta_1\{[1+\exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta\} \quad (6)$$

where G is a positive finite number. When $G \rightarrow \infty$, the last term converges to $\beta_1[I(y_{t-1} \leq f_{t-1}(\beta_1)) - \theta]$. $I(\cdot)$ represents the indicator function. The adaptive model incorporates the following aspect: whenever VaR is exceeded, the model should immediately increase it, but when it is not exceeded, the model should slightly decrease it. The strategy reduces the probability of a sequence of hits and makes it unlikely that there will never be hits.

2.3 The quantile regression

A characteristic of CAViaR is that its unknown parameters are estimated by quantile regression, as introduced by Koenker and Bassett (1978). Quantile regression is a type of regression analysis that estimates the conditional quantile of the response variable. Considering a sample of y_t observations generated by the model

$$y_t = x'_t \beta^0 + \varepsilon_{\theta t}, \quad Quant_\theta(\varepsilon_{\theta t} \mid x_t) = 0 \tag{7}$$

where x_t is a *p*-vector of regressors and $Quant_\theta(\varepsilon_{\theta t} \mid x_t)$ is the θ-quantile of $\varepsilon_{\theta t}$ conditional on x_t. Let $f_t(\beta) \equiv x_t\beta$. The θth regression quantile estimates are defined as any $\hat{\beta}(\theta)$ that solves

$$\min_{\beta} \frac{1}{T} \sum_{t=1}^{T} [\theta - I(y_t < f_t(\beta))][y_t - f_t(\beta)]. \tag{8}$$

Another specific characteristic of quantile regressions is that they include as a particular case the least absolute deviation (LAD) approach, which is more robust than ordinary least square (OLS) estimators whenever errors have a fat-tailed distribution.

In order to better analyze the estimated betas ($\hat{\beta}(\theta)$), consider the model:

$$y_t = f(y_{t-1}, x_{t-1}, \ldots, y_1, x_1; \beta^0) + \varepsilon_{t\theta} \equiv f_t(\beta^0) + \varepsilon_{t\theta} \quad t = 1, \ldots, T$$

$$[Quant_\theta(\varepsilon_{t\theta} | \Omega_t) = 0] \tag{9}$$

where $f_1(\beta^0)$ is a given initial condition, x_t is a vector of exogenous or predetermined variables, β^0 is the vector of the true unknown parameters that are needed to be estimated, and Ω_t is the information set available at time t. Assuming that $\hat{\beta}(\theta)$ is the vector of parameters that minimize (8), the work of Engle and Manganelli has provided three significant theorems that imply statistical characteristics for the nonlinear models of regression quantiles considered. The conclusion is that the estimated $\hat{\beta}(\theta)$ is consistent and asymptotically normal. Lastly, the third theorem provides a consistent estimator of the variance-covariance matrix.

3 Empirical results

3.1 Data

To implement the model, historical series of portfolio returns and a specific functional form of the quantile must be specified. The samples range from October 3, 2007 to July 31, 2020. The database used to compute the CAViaR analysis consists of daily equity returns from MSCI World ESG Leaders Index (GSIN) and the Standard & Poor 500 Index (SPX). Specifically, the GSIN Index has been used to maintain consistency between financial and ESG analyses since the extra-financial analysis has been done using the MSCI ESG Data provider. In particular, the MSCI World ESG Leaders Index is an equity capitalization-weighted index that provides high exposure to ESG performance relative to their sector peers. Aggregating MSCI regional ESG indexes constructs the index. This family of indexes uses company's ratings and research, provided by MSCI ESG, to determine eligibility for the index inclusion. The parent index is the MSCI World Index. A peculiar characteristic of the construction process is the use of the MSCI ESG Business Involvement Screening Research that permits identifying companies directly involved in specific business activities. Companies that meet the business involvement criteria are excluded from the index. Moreover, the methodology used to select companies is the Best-In-Class process. The mentioned methodology is an investment strategy used in the responsible investment process. Eurosif defines it as "*an approach where leading or best-performing investments within a universe, category or class are selected or weighted based on ESG criteria. The approach involves the selection or weighting of the best performing or most improved companies or assets as identified by ESG analysis, within a defined investment universe*" (European SRI Study, 2012, 10). Controversial businesses considered by MSCI ESG are:

- Alcohol;
- Gambling;
- Tobacco;
- Nuclear Power;
- Conventional Weapons;
- Nuclear Weapons.

The MSCI World ESG Leaders' construction uses the following regions: developed Asia Pacific; developed Europe and Middle East; Canada; USA. In the end, the index has a US country exposure of 65.71%, which makes it comparable to the Standard & Poor 500 Index. The SPX index, used as the traditional index, considers the performance of the large-cap segment of the US market. It is considered to be a proxy of the US equity market. It is constructed with the methodology of weighting constituents by float-adjusted market capitalization. It is part of the S&P US indexes, a family of equity indexes used to track US market performance, trading on US exchanges. Its index constituents are selected from the Standard & Poor Total Market Index. Additionally, a sector balance, as measured by the comparison of each Global Industry Classification Standard (GICS) sector's weight with its weight in the S&P parent index, in the relevant market capitalization range is considered.

Figures 1 & 2 contain summary statistics for the GSIN and SPX indexes.

Sample size	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
3348	0	0.0112	-0.7272	12.3173	-0.1027	0.0863

Figure 1 Summary statistics for GSIN daily returns

Sample size	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
3348	0	0.0132	-0.5456	13.5169	-0.1277	0.1096

Figure 2 Summary statistics for SPX daily returns

Negative skewness levels imply that the distribution deviates from the normal distribution. Moreover, both distributions have heavy tails since kurtosis levels are above 3. A more in-depth analysis has been conducted to analyze the difference in levels of financial risk between stocks with higher and lower ESG ratings. GSIN and SPX have, respectively, a basket of 762 and 500 constituents. More specifically, considering their constituents, twenty paired stocks were analyzed. The comparison includes one stock from GSIN and the other from SPX. The index universe of constituents was entered in the MSCI ESG platform to obtain the ESG rating and GICS sector for each stock. Then, the universe was divided by the GICS sector to have a broad, diversified, and homogeneous analysis. The GSIN index ratings are mostly "AAA" because stocks that are part of the index universe are the output of the Best-In-Class methodology. However, the SPX index has a broad ESG rating diversification. This specific characteristic permits to choose companies in the traditional index that are not prime companies when discussing sustainability. The finalists for the SPX are stocks that have an MSCI ESG rating between BBB and CCC (see Figure 10 for the MSCI ESG rating distribution). Indeed, this work focuses on the difference that stocks have in terms of ESG rating and examines if this gap is also reflected in VaR estimates. For a more in-depth insight into the MSCI ESG Methodology see the Appendix, Figure 13 better explains the ESG framework and process overview, while Figure 14 offers the MSCI ESG rating distribution. The considered pairs are:

Sector	**SPX (MSCI ESG rating)**	**GSIN (MSCI ESG rating)**
Banks	JP Morgan Chase & Co (BB)	KBC Groep NV (AAA)
Industrial Machinery	Stanley Black & Decker (BBB)	3M Company (AAA)
Pharmaceuticals	Pfizer (B)	MERCK (AAA)
Software & Services	Digital Realty Trust (BB)	Microsoft Corporation (AAA)
Telecommunication Services	CenturyLink (BB)	NTT Docomo (AAA)
Construction Materials	AO Smith Corporation (BBB)	CRH (AAA)
Retail – Food & Staples	Sysco Corporation (BBB)	UCA Gruppen (AAA)
Electronic Equipment	Emerson Electronic (BBB)	Omron Corporation (AAA)
Health Care Equipment & Supplies	Zimmer Biomet Holdings (B)	West Pharmaceutical Services (AAA)
Multi-Line Insurance & Brokerage	The Hartford Financial Services Group (BB)	Allianz (AAA)

Table 1 List of Companies from GSIN and SPX, in the respective same sector

The number of observed prices considered is 3,348 for each historical series. All of them were downloaded from Bloomberg. Daily returns were computed as the difference of the log of prices,

$$y_t = \ln \frac{p_t}{p_{t-1}} \qquad (10)$$

with y_t the return and p_t and p_{t-1} as prices at time t and t-1, respectively. Specifically, the model uses the first 2,848 observations for the in-sample estimation and the last 500 for the out-of-sample testing. The objective function of the quantile regression model is constructed to obtain the exact sample quantile with a given level. The consequence is that the in-sample empirical coverage is quite precise. The daily VaR is estimated at 1% and 5% using the following four CAViaR models: the symmetric absolute value, the asymmetric slope, the indirect GARCH, and the adaptive model. For the adaptive model, a G = 10 was used in order to get a smooth version of the step function, where G entered the definition of the adaptive model in section 2.2. Moreover, G could have been estimated but it goes against the simplicity spirit of the model.

Using the CAViaR model, to compute the VaR, I consider $f_1(\beta)$ to the empirical θ-quantile of the first 300 observations. Instruments used to compute the out-of-sample DQ test are a constant, forecasted VaR, and the first four lagged hits[4]. The DQ test is a Dynamic Quantile test which can be interpreted as an overall goodness-of-fit test for the estimated CAViaR processes.

Next, there will be a more in-depth analysis, using all the previously mentioned CAViaR models, to investigate if stocks declared to be "sustainable" through their ESG rating lower their risk compared to traditional companies.

3.2 The Results

This section provides the estimation results for all the models indicated above. In summary, the following Tables will present the value of the estimated parameters, their standard errors, the one-sided p-values, the value of the quantile regression's objective

[4] All computations were done in MATLAB 9.9, and the original code is the one released by Engle and Manganelli. The code uses functions *fminsearch* and *fminunc* as optimization algorithms.

function, the number of times (in percentage) the VaR is exceeded, and the p-value of the DQ test, both in-sample and out-of-sample for GSIN and SPX. The number of estimated parameters depends on the model considered. The first result, which remains unchanged across all estimations done across indexes and sectors considered, is that the coefficient of the autoregressive term (β_2) is always significant, which means that the phenomenon of volatility clustering is relevant also in the tail of the distribution, more specifically at the 1% and 5% of the distribution. Moreover, models that perform the best are the symmetric absolute value and the asymmetric slope. Lastly, it is interesting to notice that in the asymmetric slope model the estimated coefficients for β_4, relative to the negative part of the lagged results, are always strongly significant, while estimated coefficients β_3, relative to the positive part of the lagged returns, are sometimes not significantly different from 0. In economic terms, the strong asymmetry suggests that negative returns might have a stronger effect on VaR estimates than positive returns. Hence, it is an index of strong asymmetric impacts on VaR of lagged returns, as shown in Figure 4 below.

		Pharmaceuticals		Telecommunication Services		Retail - Food & Staples	
		PFE	MRK	LUMN	NTT	SYY	ICA
5% VaR	Beta 3	**0.0669**	**0.2305**	**0.1673**	**0.1219**	**0.0625**	**0.0984**
	Beta 4	**0.1891**	**0.3863**	**0.2421**	**0.1599**	**0.1272**	**0.1683**

Figure 3 Example of significant Beta 3 & 4, estimated using the Asymmetric Slope model, at 5% VaR

An essential foresight to consider is that VaR violations are rare events at 1% VaR.

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	SPX	GSIN	SPX	GSIN	SPX	GSIN	SPX	GSIN
1% VaR								
Beta 1	**0.0012**	**0.0008**	**0.0008**	**0.0006**	**0.0000**	**0.0000**	**-0.0001**	**-0.0001**
Standard Errors	0.0003	0.0003	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
p values	0.0001	0.0036	0.0000	0.0000	0.0002	0.0235	0.0000	0.0000
Beta 2	**0.8753**	**0.8408**	**0.9191**	**0.8941**	**0.8506**	**0.8486**		
Standard Errors	0.0407	0.0281	0.0198	0.0258	0.0079	0.0175		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.3220**	**0.4830**	0.0002	0.1331	0.8459	**1.0531**		
Standard Errors	0.1443	0.1102	0.0855	0.1182	0.5325	0.4050		
p values	0.0128	0.0000	0.4991	0.1301	0.0561	0.0047		
Beta 4			**0.4042**	**0.4252**				
Standard Errors			0.1070	0.0851				
p values			0.0001	0.0000				
RQ	1.0239	0.8863	0.9975	0.8444	1.0008	0.8806	1.5443	1.2587
Hits in-sample (%)	1.0530	1.0526	1.0179	1.0175	1.0179	1.0175	0.6669	0.7018
Hits out-of-sample (%)	1.8000	1.8000	2.0000	2.2000	1.8000	1.6000	32.4000	25.4000
DQ in-sample								
p values	0.0157	0.0259	0.2795	0.0292	0.4539	0.0259	0*	0*
DQ out-of-sample								
p values	1.50E-07*	0*	0.0252	0*	0.0575	0.0586	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 4 Summary Table for 1% VaR for Standard & Poor 500 Index VS MSCI World ESG Leaders Index

At first glance, estimated coefficients at 1% VaR are more significant than at 5% VaR (Figures 5 and 6). An interpretation is that, on average, models perform better when the considered tail is smaller. The smaller the computed VaR (θ) is, the more accurate output it is obtained. Moreover, on average estimated coefficients for the SPX Index, both at 1% and 5% VaRs, are higher than the GSIN ones. The higher estimated coefficients for the SPX Index have a higher negative incrementing impact on the VaR estimation, considering the symmetric absolute value model, the asymmetric slope model, and the indirect GARCH model. As already mentioned, VaR measures the potential expected loss at a determined significant level (θ). Estimated betas demonstrate that, assuming equal returns for both indexes, the SPX VaR at 1% and 5% is higher than GSIN VaRs. As shown in Figure 5, results at the 1% VaR show that all models do a good job describing the evolution of the left tail for the two analyzed indexes.

5% VaR	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	SPX	GSIN	SPX	GSIN	SPX	GSIN	SPX	GSIN
Beta 1	0.0002	**0.0001**	**0.0003**	**0.0003**	0.0000	0.0000	**0.0000**	**0.0000**
Standard Errors	0.0001	0.0002	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
p values	0.0981	0.1776	0.0010	0.0083	0.1370	0.0705	0.0000	0.0000
Beta 2	**0.9030**	**0.9069**	**0.9254**	**0.9185**	**0.9193**	**0.9016**		
Standard Errors	0.0107	0.0314	0.0128	0.0237	0.0121	0.0113		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.2055**	**0.1944**	**-0.0027**	0.0483	0.2282	**0.2855**		
Standard Errors	0.0251	0.0619	0.0266	0.0658	0.3532	0.1422		
p values	0.0000	0.0009	0.4593	0.2315	0.2591	0.0223		
Beta 4			**0.2635**	**0.2392**				
Standard Errors			0.0264	0.0433				
p values			0.0000	0.0000				
RQ	3.6545	3.1184	3.5603	3.0602	3.6328	3.1273	4.3335	3.7781
Hits in-sample (%)	5.0193	4.9825	5.0193	4.9474	5.0544	5.0526	3.9663	3.8947
Hits out-of-sample (%)	6.0000	4.8035	5.4000	5.0000	5.4000	5.2000	37.4000	42.8000
DQ in-sample								
p values	0.0759	0.4129	0.0726	0.9485	0.3490	0.1759	6.93E-13*	0*
DQ out-of-sample								
p values	0.1634	0.0572	0.0628	0.1430	0.0563	0.2013	0*	0*
Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level								

Figure 5 Summary Table for 5% VaR for Standard & Poor 500 Index VS MSCI World ESG Leaders Index

However, considering the 5% VaR outputs shown in Figure 6, there is a remarkable precision around the percentage of the out-of-sample hits generated by the AS model for the GSIN index. More specifically, the number of hits in-sample and out-of-sample represents the number of times VaR has been exceeded in the relative dataset considered.

Lastly, the DQ test, both in-sample and out-of-sample, can be interpreted as an overall goodness-of-fit test for the estimated CAViaR models.

A significant sector that strongly proved how vital sustainability is with regards to risk exposure is Banks. Specifically, KBC has a AAA rating, while the JP Morgan's rating is BB. They have four notches of differences. It is perfectly reflected in the data, as shown in Figure 7. The p-values show that all beta estimates for KBC are significant at 5%, while JP Morgan's estimates are not. Moreover, there is a relevant precision in the percentage of out-of-sample hits generated at the 1% VaR for KBC by the SAV and AS models.

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	JPM	KBC	JPM	KBC	JPM	KBC	JPM	KBC
1% VaR								
Beta 1	0.0006	**0.0020**	0.0011	**0.0018**	**0.0001**	**0.0001**	**-0.0002**	**-0.0002**
Standard Errors	0.0004	0.0007	0.0012	0.0010	0.0000	0.0000	0.0000	0.0000
p values	0.0806	0.0012	0.1718	0.0400	0.0019	0.0226	0.0000	0.0000
Beta 2	**0.9264**	**0.8196**	**0.8975**	**0.8568**	**0.9000**	**0.8889**		
Standard Errors	0.0295	0.0164	0.0581	0.0346	0.0084	0.0152		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.2228**	**0.5303**	0.0940	**0.2702**	0.5399	**0.6650**		
Standard Errors	0.0837	0.0440	0.1331	0.0919	0.3730	0.0813		
p values	0.0039	0.0000	0.2400	0.0016	0.0739	0.0000		
Beta 4			**0.4665**	**0.5181**				
Standard Errors			0.1518	0.0500				
p values			0.0011	0.0000				
RQ	2.0578	2.7259	1.9779	2.6606	2.0583	2.7067	2.9105	3.8735
Hits in-sample (%)	1.0179	1.0175	0.9828	1.0175	1.0179	1.0175	0.6318	0.8070
Hits out-of-sample (%)	1.2000	1.0000	0.8000	1.0000	1.0000	0.8000	56.2000	45.2000
DQ in-sample								
p values	0.0386	0.6910	0.0130	0.6168	0.00044*	0.3914	0.042*	0*
DQ out-of-sample								
p values	0.01096*	0*	0.9840	7.22E-07*	0.9989	0.00039*	0*	0*
Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level								

Figure 6 Summary Table for 1% VaR for JPMORGAN CHASE & CO.VS KBC Groep NV, Banks sector

Considering the same sector, outputs at the 5% VaR in Figure 8 show that, in the AS model, estimates for β_4 for both JP Morgan and KBC are significant, and they are more than twice the estimates for β_3. As already mentioned, it means that there is a strong asymmetric impact on VaR lagged returns.

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	JPM	KBC	JPM	KBC	JPM	KBC	JPM	KBC
5% VaR								
Beta 1	**0.0004**	0.0007	**0.0003**	**0.0018**	**0.0000**	0.0000	**-0.0001**	**-0.0001**
Standard Errors	0.0001	0.0007	0.0001	0.0005	0.0000	0.0000	0.0000	0.0000
p values	0.0040	0.1595	0.0004	0.0002	0.0039	0.1870	0.0000	0.0000
Beta 2	**0.9353**	**0.8306**	**0.9313**	**0.8005**	**0.9165**	**0.8557**		
Standard Errors	0.0081	0.0261	0.0160	0.0177	0.0057	0.0093		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1097**	**0.3487**	**0.0547**	**0.2119**	**0.1660**	0.4291		
Standard Errors	0.0215	0.0212	0.0182	0.0251	0.0395	0.4547		
p values	0.0000	0.0000	0.0013	0.0000	0.0000	0.1726		
Beta 4			**0.1889**	**0.5084**				
Standard Errors			0.0884	0.0174				
p values			0.0163	0.0000				
RQ	6.6787	9.4522	6.6142	9.2148	6.6611	9.2984	7.9983	10.9351
Hits in-sample (%)	5.0193	5.0175	4.9842	5.0175	5.0895	4.9123	4.3173	5.2982
Hits out-of-sample (%)	5.6000	4.8000	5.4000	4.6000	6.4000	4.2000	46.0000	33.2000
DQ in-sample								
p values	0.00017*	0.0066*	0.0012*	0.7126	0.1074	0.1124	1.27E-11*	0*
DQ out-of-sample								
p values	2.97E-12*	0.2563	0.0001*	0.9668	2.99E-08*	0.2641	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 7 Summary Table for 5% VaR for JPMORGAN CHASE & CO.VS KBC Groep NV, Banks sector

The last analyzed sector is the Health Care Equipment & Supplies one, which has significantly different outputs for the two companies; see Figure 9. Zimmer Biomet Holdings has a “B” rating, while West Pharmaceutical Services has a “AAA” rating. In this case, the two stocks have four notches of difference. For WST, estimated coefficients are almost all significant, which is not the case for ZBH. However, the number of out-of-sample hits is very low for both companies, especially since the considered VaR is at 1%, which makes this phenomenon rarer.

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	ZBH	WST	ZBH	WST	ZBH	WST	ZBH	WST
1% VaR								
Beta 1	0.0014	**0.0010**	0.0018	**0.0013**	0.0001	0.0000	**-0.0001**	**-0.0001**
Standard Errors	0.0022	0.0004	0.0029	0.0005	0.0001	0.0000	0.0000	0.0000
p values	0.2583	0.0036	0.2654	0.0054	0.2073	0.0801	0.0000	0.0000
Beta 2	**0.8421**	**0.9047**	**0.8416**	**0.8873**	0.7849	**0.9600**		
Standard Errors	0.1478	0.0232	0.1727	0.0286	0.1185	0.0069		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	0.4953	**0.2446**	0.3714	**0.2569**	1.7142	**0.2003**		
Standard Errors	0.3962	0.0680	0.4423	0.0631	3.8280	0.0459		
p values	0.1056	0.0002	0.2005	0.0000	0.3272	0.0000		
Beta 4			0.5383	**0.3059**				
Standard Errors			0.4836	0.1260				
p values			0.1328	0.0076				
RQ	1.7444	1.4451	1.7362	1.4408	1.7931	1.4681	2.1477	1.7593
Hits in-sample (%)	0.9828	1.0175	0.9828	1.0175	0.9828	1.0175	0.6318	0.5965
Hits out-of-sample (%)	1.0000	1.2000	0.8000	1.2000	0.8000	1.2000	20.8000	13.0000
DQ in-sample								
p values	0.9178	0.6775	0.9038	0.6786	0.9221	0.6881	0.0662	0.1154
DQ out-of-sample								
p values	0.9784	0.9760	0.9953	0.9437	0.9971	0.9961	0*	0*
Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level								

Figure 8 Summary Table for 1% VaR for ZIMMER BIOMET HOLDINGS VS West Pharmaceutical Services, Health Care Equipment & Supplies sector

4 Conclusion

In this paper, we employ several CAViaR models in order to analyse whether there is a reduction in risk levels given by the fact that the financial instrument has a higher MSCI ESG rating. However, the conclusion is that there is no significant and enough evidence showing a reduction in risk exposure. When significant beta estimates in the symmetric absolute value and asymmetric slope models have a positive impact on reducing exposure. The CAViaR model proved to perform nicely across different sectors and indexes. Nonetheless, the considered in-sample data set mostly look at a sample in which observations coming from a period of stress in the market are the minority. The only crisis considered is the Global Financial Crisis. Thus, the COVID-19 observations fall within the out-of-sample data set. The model has been empirically proved to nicely perform under calm financial market conditions. The model gave significant results for the specific sectors and indexes considered.

However, because of its innovative and useful nature, the CAViaR model has been analyzed, improved, and tested over the years, under different financial market conditions. There has been empirical evidence that the implicit dynamic nature of the CAViaR model requires considerable precision for the parameter estimation. Moreover, when implemented, CAViaR faces some challenges due to its regression model's characteristics. It assigns the same weight to each observation, and the estimation of the model's parameters may heavily depend on the sample's length. These characteristics are significant when considering using the model to describe the riskiness of an asset. The first empirical analysis was performed by Bao et al. (2006) on five East and Southeast Asian markets. The analysis was performed considering three out-of-sample evaluation periods: before the crisis, during the crisis, and after the crisis. Researchers concluded that risk forecasts using the CAViaR methodology yielded lower results during the crisis period than during stress-free periods; none of the four CAViaR models gave a significant performance when the sample considered a period of stress. Moreover, Kuester et al. (2006) provided empirical evidence confirming that the presence of volatile years results in the deterioration of the overall performance of CAViaR. All the results conclude that the model might lose some capabilities when dealing with data that are subject to exogenous influence and spillover effects.

Regarding the ESG analysis, results show a significant difference between traditional and sustainable companies. There is evidence that when the stock has a higher MSCI ESG rating, it has lower estimated betas, which impact less on the final computation of VaR. It reflects a higher level of stock's quality. MSCI ESG Rating is the final output which incorporates a series of analysis done by the Data Provider itself, and a significant amount of ESG data coming from the non-financial statement, provided by the analysed company. The main sources which contributes to the final rating output are specialized datasets such as governments, NGOs, models; company reports such as the non-financial statements, sustainability reports, the code of conduct; and many different media sources, which are monitored daily, such as global and local news sources. Thus, a risk reduction can be explained by the fact that companies, by displaying ESG data through their non-financial statement, invest time and money in trying to lower information asymmetry with investors on the financial market, giving them the possibility to better assess the company's risk and its valuation. The reputational risk of a company can be easily monitored by the financial market. The effort a company invests is then reflected and payed back by a lower level of volatility of return rates, which reduces investment portfolio risk, understood as return rate volatility. If a client decides to invest his money in a sustainable portfolio, he will have a positive impact on his own portfolio, by reducing its risk exposure but, most importantly from my point of view, he will have a less impactful investment on the environment around him. Investing in sustainability does not necessarily mean that there is no impact on the environment because a zero-impact approach, given the globalized world we live in, is very difficult to reach. However, putting some effort in understanding how sustainable the companies are the investor is financing, can be important in order to preserve his money and the world for the next generations.

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Appendix

	2014	2016	2018
Europe	58.8%	52.6%	48.8%
United States	17.9%	21.6%	25.7%
Canada	31.3%	37.8%	50.6%
Australia/New Zealand	16.6%	50.6%	63.2%
Japan		3.4%	18.3%

Figure 9 Proportion of Sustainable Investing Assets relative to Total Managed assets in the period 2014-2018, Global Sustainable Investment Alliance

Region	2016	2018
Europe	$ 12,040	$ 14,075
United States	$ 8,723	$ 11,995
Japan	$ 474	$ 2,180
Canada	$ 1,086	$ 1,699
Australia/New Zealand	$ 516	$ 734
TOTAL	**$ 22,890**	**$ 30,683**

Note: Asset values are expressed in billions of US dollars. All 2016 assets are converted to US dollars at the exchange rates as of year-end 2015. All 2018 assets are converted to US dollars at the exchange rates at the time of reporting.

Figure 10 Snapshot of Global Sustainable assets in the period 2016-2018, Global Sustainable Investment Alliance

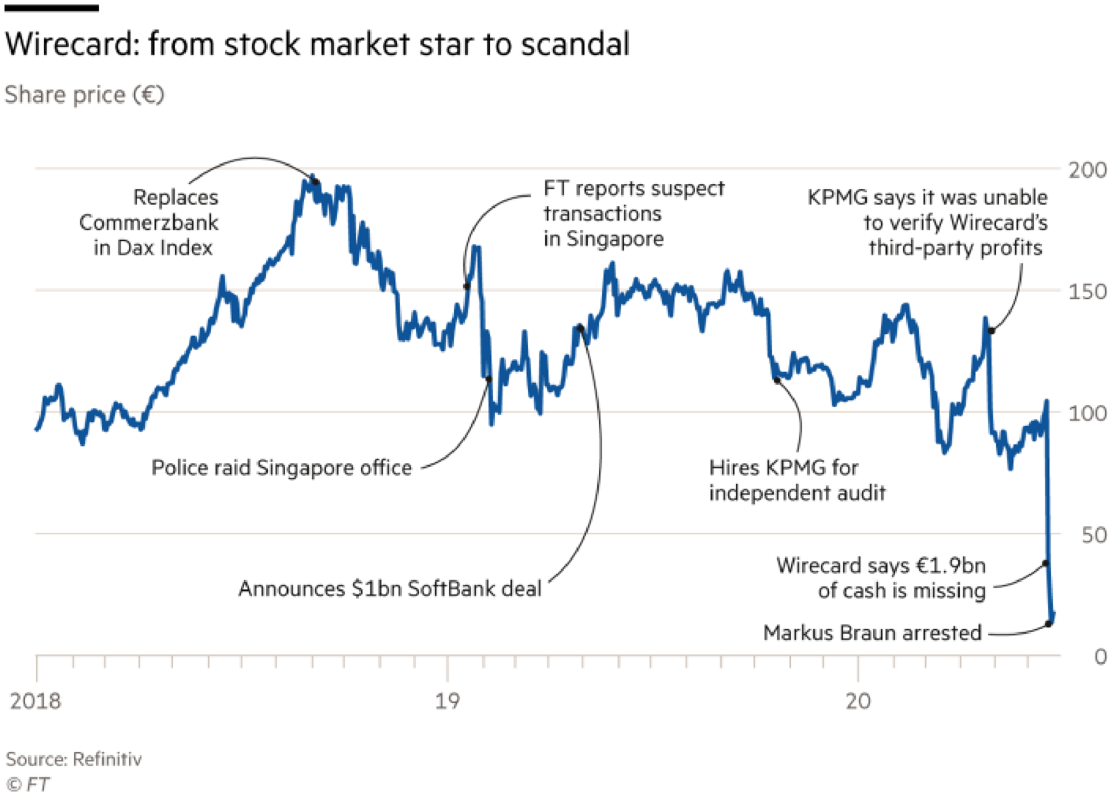

Figure 11: Wirecard Share Price performance from January 2019 until June 2020

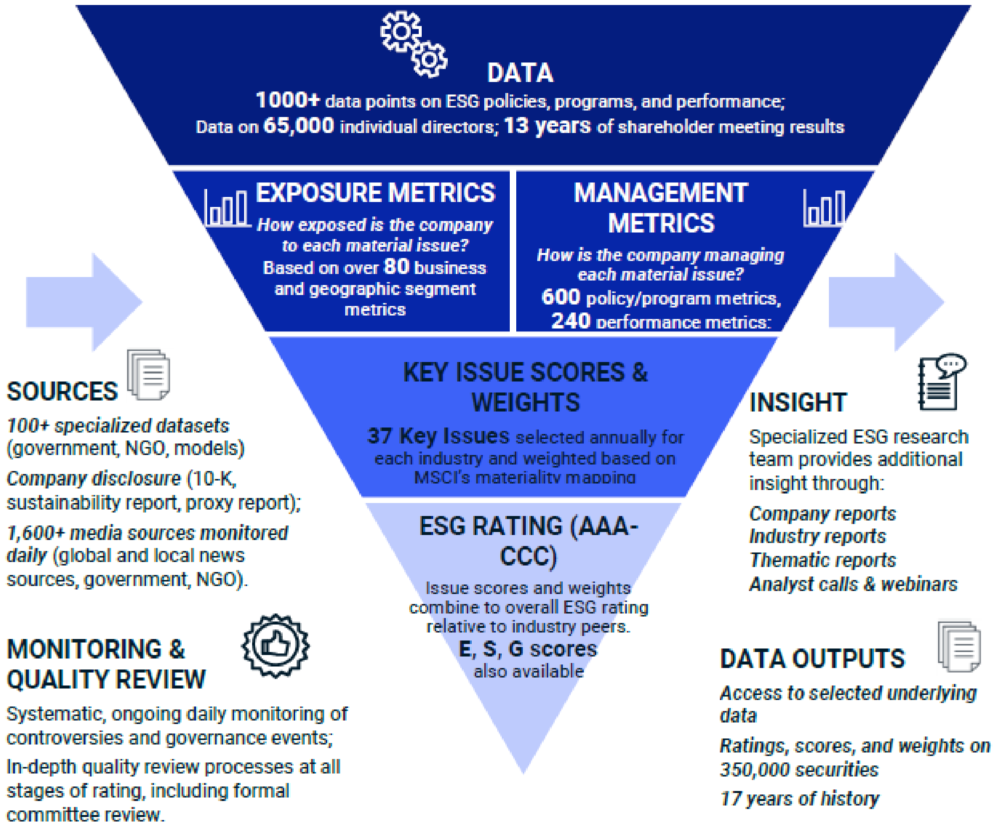

Figure 12 ESG Rating Framework and Process Overview

Figure 13 MSCI ESG Rating Distribution

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	SWK	MMM	SWK	MMM	SWK	MMM	SWK	MMM
1% VaR								
Beta 1	**0.0017**	**0.0013**	**0.0013**	**0.0009**	**0.0001**	**0.0000**	**-0.0001**	**0.0000**
Standard Errors	0.0009	0.0007	0.0005	0.0003	0.0000	0.0000	0.0000	0.0000
p values	0.0243	0.0223	0.0031	0.0006	0.0145	0.0177	0.0000	0.0000
Beta 2	**0.8863**	**0.9075**	**0.9275**	**0.9405**	**0.8889**	**0.9199**		
Standard Errors	0.0390	0.0246	0.0245	0.0154	0.0164	0.0145		
p values	0.0000	0.0000	1.55E-313	0.0000	0.0000	0.0000		
Beta 3	**0.2591**	**0.2105**	-0.0401	0.0128	0.4772	0.4048		
Standard Errors	0.0855	0.0328	0.0406	0.0434	0.5345	0.4154		
p values	0.0012	0.0000	0.1616	0.3844	0.1860	0.1649		
Beta 4			**0.3049**	**0.2412**				
Standard Errors			0.0618	0.0387				
p values			0.0000	0.0000				
RQ	1.6133	1.3357	1.5522	1.3098	1.6449	1.3443	2.1161	1.6164
Hits in-sample (%)	0.9828	1.0526	0.9828	1.0526	0.9828	0.9825	0.6318	0.7368
Hits out-of-sample (%)	2.2000	2.4000	2.2000	2.4000	2.4000	2.2000	18.3000	14.0000
DQ in-sample								
p values	0.3795	0.4964	0.6545	0.7646	0.3521	0.3604	0.0491	0.0315
DQ out-of-sample								
p values	0.0193	0.0016*	0.0192	0.0016*	0.0089*	0.00090*	0*	0*
5% VaR								
Beta 1	**0.0004**	0.0002	**0.0003**	**0.0002**	**0.0000**	0.0000	**0.0000**	**0.0000**
Standard Errors	0.0001	0.0002	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
p values	0.0018	0.2238	0.0000	0.0017	0.0087	0.0427	0.0000	0.0000
Beta 2	**0.9210**	**0.9190**	**0.9501**	**0.9546**	**0.9227**	**0.8957**		
Standard Errors	0.0182	0.0259	0.0062	0.0115	0.0106	0.0072		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1315**	**0.1600**	-0.0063	0.0003	0.1660	**0.2574**		
Standard Errors	0.0317	0.0443	0.0156	0.0210	0.2709	0.1166		
p values	0.0000	0.0002	0.3430	0.4938	0.2700	0.0137		
Beta 4			**0.1828**	**0.1601**				
Standard Errors			0.0125	0.0324				
p values			0.0000	0.0000				
RQ	5.3148	4.3276	5.1796	4.2540	5.3520	4.3240	5.9509	4.7852
Hits in-sample (%)	5.0193	4.9825	5.0544	4.9825	5.0193	4.9474	4.7385	4.5614
Hits out-of-sample (%)	7.4000	6.4000	5.8000	6.0000	6.6000	6.8000	27.9000	27.0000
DQ in-sample								
p values	0.00096*	0.1581	0.9629	0.2846	0.0083*	0.8060	0.000014*	0.00014*
DQ out-of-sample								
p values	2.76E-06*	0.1073	0.0477	0.4145	6.68E-07*	0.0847	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 14 Summary Table for Stanley Black & Decker VS 3M Company, Industrial Machinery sector

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	PFE	MRK	PFE	MRK	PFE	MRK	PFE	MRK
1% VaR								
Beta 1	**0.0019**	**0.0032**	**0.0011**	**0.0032**	**0.0001**	0.0168	**-0.0001**	**-0.0001**
Standard Errors	0.0004	0.0014	0.0005	0.0014	0.0000	0.0001	0.0000	0.0000
p values	0.0000	0.0117	0.0188	0.0143	0.0001	0.0834	0.0000	0.0000
Beta 2	**0.8272**	**0.7477**	**0.8579**	**0.7538**	**0.7732**	**0.7225**		
Standard Errors	0.0340	0.0686	0.0427	0.0987	0.0171	0.0328		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.4211**	**0.6128**	**0.2757**	0.5865	**1.1604**	1.7062		
Standard Errors	0.1163	0.1609	0.1481	0.5996	0.3376	4.1679		
p values	0.0001	0.0001	0.0313	0.1640	0.0003	0.3411		
Beta 4			**0.4923**	**0.6101**				
Standard Errors			0.0908	0.1812				
p values			0.0000	0.0004				
RQ	1.1722	1.5723	1.1590	1.5722	1.1520	1.5755	1.5262	2.1057
Hits in-sample (%)	1.0530	1.0175	0.9828	1.0175	1.0179	0.9825	0.7020	0.5614
Hits out-of-sample (%)	2.2000	1.8000	1.8000	1.8000	2.8000	2.2000	24.4000	39.4000
DQ in-sample								
p values	0.0346	0.0273	0.7406	0.0259	0.0228	0.6350	0.000024*	0.000048*
DQ out-of-sample								
p values	0.0049*	0.2163*	5.48E-09*	0.2232	0.00058*	0.0168	0*	0*
5% VaR								
Beta 1	0.0002	0.0008	0.0002	**0.0011**	0.0000	**0.0000**	**0.0000**	**0.0000**
Standard Errors	0.0002	0.0006	0.0002	0.0004	0.0000	0.0000	0.0000	0.0000
p values	0.1491	0.0670	0.0651	0.0012	0.1936	0.0039	0.0000	0.0000
Beta 2	**0.9306**	**0.8050**	**0.9296**	**0.7978**	**0.9268**	**0.7203**		
Standard Errors	0.0288	0.0408	0.0183	0.0396	0.0096	0.0318		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1309**	**0.3267**	**0.0669**	**0.2305**	0.1766	**0.5844**		
Standard Errors	0.0553	0.1009	0.0383	0.0777	0.1327	0.2754		
p values	0.0090	0.0006	0.0404	0.0015	0.0916	0.0169		
Beta 4			**0.1891**	**0.3863**				
Standard Errors			0.0466	0.0657				
p values			0.0000	0.0000				
RQ	4.0611	4.6968	4.0320	4.6743	4.0467	4.7201	4.4734	5.5954
Hits in-sample (%)	5.0193	4.9474	5.0193	4.9825	5.0544	5.0526	4.4226	3.7544
Hits out-of-sample (%)	6.8000	6.0000	6.0000	6.4000	6.2000	6.2000	26.2000	31.8000
DQ in-sample								
p values	0.1539	0.8337	0.5932	0.9852	0.2942	0.6983	3.09E-06*	0*
DQ out-of-sample								
p values	0.0230	0.4855	0.1597	0.1297	0.1438	0.1661	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 15 Summary Table for Pfizer VS MERCK, Pharmaceuticals sector

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	DLR	MSFT	DLR	MSFT	DLR	MSFT	DLR	MSFT
1% VaR								
Beta 1	**0.0018**	0.0023	**0.0018**	**0.0021**	**0.0002**	0.0001	**-0.0001**	**0.0000**
Standard Errors	0.0005	0.0016	0.0006	0.0013	0.0001	0.0001	0.0000	0.0000
p values	0.0003	0.0809	0.0025	0.0447	0.0027	0.1565	0.0000	0.0000
Beta 2	**0.8707**	**0.8078**	**0.8602**	**0.8259**	**0.7632**	**0.7440**		
Standard Errors	0.0228	0.0422	0.0360	0.0315	0.0172	0.0738		
p values	000000000000€	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.3205**	**0.4938**	**0.3043**	**0.5510**	1.0289	1.4295		
Standard Errors	0.0621	0.1971	0.0764	0.1461	2.4860	1.4514		
p values	0.0000	0.0061	0.0000	0.0001	0.3395	0.1623		
Beta 4			0.4052	**0.3378**				
Standard Errors			0.2576	0.1330				
p values			0.0579	0.0055				
RQ	1.8962	1.6009	1.8929	1.5846	1.8789	1.6103	2.5553	1.8234
Hits in-sample (%)	1.0179	1.0175	1.0179	0.9825	0.9828	1.0175	0.7020	0.8070
Hits out-of-sample (%)	1.6000	1.4000	1.8000	1.4000	1.4000	1.4000	28.8000	10.2000
DQ in-sample								
p values	0.9302	0.6752	0.9431	0.6497	0.9330	0.6693	1.85E-09*	0.0049*
DQ out-of-sample								
p values	0.6806	0.9866	0.3870	0.0410	0.9003	0.9896	0*	0*
5% VaR								
Beta 1	0.0003	**0.0007**	0.0003	**0.0006**	0.0000	**0.0000**	**0.0000**	**0.0000**
Standard Errors	0.0002	0.0002	0.0002	0.0001	0.0000	0.0000	0.0000	0.0000
p values	0.1316	0.0002	0.1176	0.0000	0.2025	0.0000	0.0000	0.0000
Beta 2	**0.9101**	**0.8661**	**0.9084**	**0.8933**	**0.8847**	**0.8576**		
Standard Errors	0.0283	0.0212	0.0228	0.0147	0.0157	0.0067		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1750**	**0.2254**	**0.1877**	**0.1128**	**0.2889**	**0.2781**		
Standard Errors	0.0464	0.0343	0.0528	0.0372	0.1491	0.0597		
p values	0.0001	0.0000	0.0002	0.0012	0.0263	0.0000		
Beta 4			**0.1697**	**0.2416**				
Standard Errors			0.0463	0.0294				
p values			0.0001	0.0000				
RQ	6.2043	5.0597	6.2036	5.0365	6.1673	5.1186	7.3597	6.1188
Hits in-sample (%)	5.0193	5.0175	4.9842	5.0175	4.9842	5.0175	4.4226	3.5439
Hits out-of-sample (%)	5.4000	5.8000	5.6000	6.0000	6.2000	6.0000	30.0000	32.6000
DQ in-sample								
p values	0.2622	0.7279	0.2656	0.6625	0.8363	0.4165	1.65E-08*	1.70E-07*
DQ out-of-sample								
p values	0.8929	0.4488	0.8368	0.4824	0.6165	0.5053	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 16 Summary Table for Digital Realty Trust VS Microsoft Corporation, Software & Services sector

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	LUMN	NTT	LUMN	NTT	LUMN	NTT	LUMN	NTT
1% VaR								
Beta 1	**0.0045**	**0.0011**	**0.0047**	**0.0014**	0.0002	0.0001	**0.0000**	**-0.0001**
Standard Errors	0.0016	0.0005	0.0018	0.0006	0.0001	0.0001	0.0000	0.0000
p values	0.0030	0.0162	0.0046	0.0068	0.0173	0.0531	0.0000	0.0000
Beta 2	**0.7428**	**0.8400**	**0.7416**	**0.8382**	**0.7568**	**0.6406**		
Standard Errors	0.0487	0.0331	0.0548	0.0420	0.0413	0.0647		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.6230**	**0.4621**	**0.5705**	0.2695	1.1536	**2.2749**		
Standard Errors	0.1978	0.1492	0.3415	0.1814	0.8981	0.5806		
p values	0.0008	0.0010	0.0474	0.0688	0.0995	0.0000		
Beta 4			**0.6758**	**0.7016**				
Standard Errors			0.2332	0.0995				
p values			0.0019	0.0000				
RQ	2.0350	1.4200	2.0339	1.3809	2.0291	1.4209	2.4765	1.8428
Hits in-sample (%)	1.0179	0.9825	1.0530	0.9825	0.9828	0.9825	0.6669	0.7368
Hits out-of-sample (%)	2.4000	1.0000	2.4000	0.8000	2.2000	0.8000	5.4000	10.0000
DQ in-sample								
p values	0.6770	0.0417	0.6938	0.0249	0.9205	0.6942	1.10E-10*	0.1226
DQ out-of-sample								
p values	0.0120	0.9998	0.0128	0.9979	0.0549	0.9995	0*	0*
5% VaR								
Beta 1	**0.0006**	0.0001	**0.0005**	0.0001	**0.0000**	0.0000	**0.0000**	**0.0000**
Standard Errors	0.0002	0.0001	0.0002	0.0002	0.0000	0.0000	0.0000	0.0000
p values	0.0011	0.1586	0.0065	0.2184	0.0244	0.0563	0.0000	0.0000
Beta 2	**0.8804**	**0.9283**	**0.8876**	**0.9286**	**0.7993**	**0.9365**		
Standard Errors	0.0119	0.0096	0.0145	0.0110	0.0330	0.0059		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.2182**	**0.1377**	**0.1673**	**0.1219**	0.3904	0.1290		
Standard Errors	0.0253	0.0101	0.0462	0.0276	0.3618	0.1972		
p values	0.0000	0.0000	0.0001	0.0000	0.1402	0.2565		
Beta 4			**0.2421**	**0.1599**				
Standard Errors			0.0249	0.0296				
p values			0.0000	0.0000				
RQ	5.7752	4.4919	5.7608	4.4881	5.8590	4.5244	6.9658	5.1392
Hits in-sample (%)	4.9842	5.0175	4.9842	5.0175	5.0193	5.0877	3.5802	4.0000
Hits out-of-sample (%)	7.8000	5.8000	7.6000	5.0000	7.6000	4.8000	21.6000	15.8000
DQ in-sample								
p values	0.2175	0.000006*	0.1019	0.0106	0.7156	0.0018*	1.17E-10*	0.000025*
DQ out-of-sample								
p values	0.00065*	0.1670	0.0074*	0.5281	0.0437	0.7504	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 17 Summary Table for Centurylink VS NTT Docomo, Telecommunication Services sector

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	AOS	CRH	AOS	CRH	AOS	CRH	AOS	CRH
1% VaR								
Beta 1	**0.0024**	0.0005	**0.0042**	0.0006	**0.0001**	0.0001	**-0.0001**	**-0.0001**
Standard Errors	0.0012	0.0008	0.0012	0.0009	0.0000	0.0001	0.0000	0.0000
p values	0.0243	0.2472	0.0002	0.2449	0.0022	0.1926	0.0000	0.0000
Beta 2	**0.8594**	**0.9001**	**0.8058**	**0.8899**	**0.9165**	**0.8456**		
Standard Errors	0.0548	0.0238	0.0553	0.0308	0.0106	0.0300		
p values	0.0000	9.04e-313	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.3000**	**0.3153**	0.2126	**0.3649**	**0.3156**	**0.9334**		
Standard Errors	0.1228	0.0494	0.1816	0.0958	0.1368	0.3948		
p values	0.0073	0.0000	0.1209	0.0001	0.0105	0.0090		
Beta 4			**0.5437**	**0.3171**				
Standard Errors			0.1490	0.0441				
p values			0.0001	0.0000				
RQ	1.6769	1.9992	1.6426	1.9976	1.6562	1.9812	1.9958	2.3114
Hits in-sample (%)	1.0179	0.9825	1.0530	0.9474	0.9828	0.9825	0.7020	0.6667
Hits out-of-sample (%)	1.8000	1.4000	1.4000	1.4000	2.2000	1.4000	16.0000	31.8000
DQ in-sample								
p values	0.4933	0.6602	0.0131	0.6374	0.3089	0.6488	0.0004*	0.00006*
DQ out-of-sample								
p values	0.1142	8.98E-13*	0.4700	8.76E-13*	0.1319	4.75E-10*	0*	0*
5% VaR								
Beta 1	0.0002	0.0000	**0.0002**	0.0000	**0.0000**	0.0000	**0.0000**	**0.0000**
Standard Errors	0.0001	0.0002	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
p values	0.0565	0.4150	0.0249	0.4863	0.0404	0.4282	0.0000	0.0000
Beta 2	**0.9325**	**0.9688**	**0.9420**	**0.9713**	**0.9259**	**0.9677**		
Standard Errors	0.0134	0.0072	0.0072	0.0081	0.0050	0.0055		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1282**	**0.0687**	**0.0647**	**0.0528**	0.1756	0.0837		
Standard Errors	0.0352	0.0223	0.0145	0.0316	0.1334	0.1449		
p values	0.0001	0.0010	0.0000	0.0471	0.0940	0.2818		
Beta 4			**0.1524**	**0.0693**				
Standard Errors			0.0308	0.0229				
p values			0.0000	0.0012				
RQ	5.7445	6.9719	5.7081	6.9711	5.7132	6.9868	6.3914	7.2504
Hits in-sample (%)	5.0544	4.9825	5.0544	4.9474	4.9842	4.9474	4.0365	4.7719
Hits out-of-sample (%)	7.6000	6.2000	7.4000	6.4000	8.4000	6.2000	30.2000	20.6000
DQ in-sample								
p values	0.0556	0.8754	0.3397	0.9129	0.1296	0.6875	6.25E-08*	0.00018*
DQ out-of-sample								
p values	0.0083*	0.000009*	0.00087*	0.000018*	0.00003*	9.88E-06*	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 183 Summary Table for A. O. Smith Corporation VS CRH, Construction Materials sector

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	SYY	ICA	SYY	ICA	SYY	ICA	SYY	ICA
1% VaR								
Beta 1	0.0011	0.0025	0.0009	0.0021	**0.0000**	0.0001	**0.0000**	**0.0000**
Standard Errors	0.0007	0.0023	0.0006	0.0020	0.0000	0.0000	0.0000	0.0000
p values	0.0543	0.1345	0.0515	0.1438	0.0247	0.0676	0.0000	0.0000
Beta 2	**0.9232**	**0.8917**	**0.9199**	**0.9051**	**0.9363**	**0.9287**		
Standard Errors	0.0313	0.0754	0.0345	0.0719	0.0143	0.0245		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	2.3398e-314		
Beta 3	**0.1544**	**0.2140**	0.2133	0.0822	0.2502	0.2974		
Standard Errors	0.0419	0.1160	0.1523	0.1449	0.1938	0.9200		
p values	0.0001	0.0325	0.0807	0.2852	0.0983	0.3732		
Beta 4			**0.1420**	**0.3029**				
Standard Errors			0.0364	0.1158				
p values			0.0000	0.0045				
RQ	1.2848	1.7160	1.2825	1.6978	1.3022	1.7358	1.5299	1.8297
Hits in-sample (%)	0.9828	1.0175	1.0179	0.9825	1.0179	1.0175	0.7020	0.7018
Hits out-of-sample (%)	2.0000	0.8000	2.2000	1.0000	1.8000	0.8000	14.8000	4.4000
DQ in-sample								
p values	0.9284	0.9381	0.9157	0.9391	0.6789	0.8941	0.0786	0.3018
DQ out-of-sample								
p values	1.11E-16*	0.9995	2.22E-15*	0.9916	0*	0.9963	0*	0*
5% VaR								
Beta 1	0.0001	0.0002	**0.0001**	**0.0003**	0.0000	**0.0000**	**0.0000**	**0.0000**
Standard Errors	0.0001	0.0001	0.0001	0.0002	0.0000	0.0000	0.0000	0.0000
p values	0.0673	0.0540	0.0053	0.0236	0.3418	0.0179	0.0000	0.0000
Beta 2	**0.9472**	**0.9449**	**0.9500**	**0.9235**	**0.9665**	**0.9279**		
Standard Errors	0.0093	0.0106	0.0040	0.0228	0.0067	0.0066		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1043**	**0.1029**	**0.0625**	**0.0984**	0.0777	0.1459		
Standard Errors	0.0250	0.0201	0.0203	0.0164	0.1206	0.1280		
p values	0.0000	0.0000	0.0011	0.0000	0.2598	0.1271		
Beta 4			**0.1272**	**0.1683**				
Standard Errors			0.0125	0.0776				
p values			0.0000	0.0151				
RQ	3.9616	5.1891	3.9495	5.1751	4.0546	5.2455	4.3442	5.3889
Hits in-sample (%)	5.0193	5.0175	5.0193	5.0175	4.9140	4.9825	4.0716	4.4912
Hits out-of-sample (%)	5.4000	5.2000	4.8000	5.8000	3.8000	4.0000	25.8000	24.6000
DQ in-sample								
p values	0.4037	0.000038*	0.6118	0.0097*	0.0370	0.0081*	1.40E-09*	0.000053*
DQ out-of-sample								
p values	0.00052*	0.7838	0.0541	0.3339	0.00023*	0.8248	0*	0*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 19 Summary Table for SYSCO Corporation VS ICA Gruppen Aktiebolag, Retail – Food & Staples sector

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	EMR	6645	EMR	6645	EMR	6645	EMR	6645
1% VaR								
Beta 1	0.0009	**0.0021**	0.0007	0.0013	**0.0000**	**0.0001**	**0.0000**	**-0.0001**
Standard Errors	0.0008	0.0011	0.0006	0.0009	0.0000	0.0001	0.0000	0.0000
p values	0.1358	0.0237	0.1046	0.0675	0.0888	0.1288	0.0000	0.0000
Beta 2	**0.9090**	**0.9086**	**0.9489**	**0.9187**	**0.9214**	**0.9063**		
Standard Errors	0.0387	0.0245	0.0267	0.0252	0.0221	0.0268		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.2528**	**0.1971**	0.0035	**0.1584**	0.4142	0.4127		
Standard Errors	0.0635	0.0399	0.1503	0.0486	0.9787	1.0115		
p values	0.0000	0.0000	0.4908	0.0006	0.3361	0.3416		
Beta 4			**0.2388**	**0.2430**				
Standard Errors			0.1044	0.0625				
p values			0.0111	0.0001				
RQ	1.5560	1.9723	1.5472	1.9668	1.5418	1.9663	1.7485	2.3734
Hits in-sample (%)	0.9828	1.0179	1.0179	0.9828	1.0179	1.0179	0.9126	0.7020
Hits out-of-sample (%)	1.7000	0.9000	1.9000	0.7000	1.5000	1.1000	10.8000	3.9000
DQ in-sample								
p values	0.3872	0.9044	0.3825	0.9096	0.7158	0.8995	0.2771	0.00087*
DQ out-of-sample								
p values	NaN	0.9998	NaN	0.9936	NaN	0.9461	NaN	6.55E-11*
5% VaR								
Beta 1	0.0005	0.0004	**0.0006**	**0.0005**	**0.0000**	0.0000	**0.0000**	**0.0000**
Standard Errors	0.0003	0.0004	0.0003	0.0003	0.0000	0.0000	0.0000	0.0000
p values	0.0570	0.1594	0.0177	0.0420	0.0102	0.1883	0.0000	0.0000
Beta 2	**0.9234**	**0.9426**	**0.9259**	**0.9435**	**0.9317**	**0.9267**		
Standard Errors	0.0260	0.0151	0.0253	0.0117	0.0095	0.0142		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1247**	**0.0993**	0.0318	0.0420	0.1419	0.1613		
Standard Errors	0.0505	0.0235	0.0587	0.0268	0.1884	0.1199		
p values	0.0068	0.0000	0.2942	0.0583	0.2257	0.0892		
Beta 4			**0.2011**	**0.1414**				
Standard Errors			0.0511	0.0274				
p values			0.0000	0.0000				
RQ	5.3167	6.8344	5.2549	6.8041	5.3027	6.8021	5.9343	7.1986
Hits in-sample (%)	4.9842	4.9842	4.9842	4.9842	4.9491	5.0193	4.0716	4.5981
Hits out-of-sample (%)	6.4000	4.6000	6.4000	4.4000	6.4000	4.2000	23.3000	12.5000
DQ in-sample								
p values	0.5256	0.5746	0.6789	0.3747	0.4299	0.4034	1.76E-06*	5.56E-08*
DQ out-of-sample								
p values	NaN	0.8367	NaN	0.5253	NaN	0.1572	NaN	1.29E-14*

Note: significant coefficient at 5% formatted in bold; "*" denotes rejection from the DQ test at 1% significance level

Figure 20 Summary Table for EMERSON ELECTRIC CO. VS OMRON Corporation, Electronic Equipment sector

	Symmetric Absolute Value		Asymmetric Slope		Indirect GARCH		Adaptive	
	HIG	ALV	HIG	ALV	HIG	ALV	HIG	ALV
1% VaR								
Beta 1	**0.0007**	0.0009	0.0005	0.0008	**0.0000**	0.0000	**-0.0012**	**-0.0001**
Standard Errors	0.0004	0.0006	0.0004	0.0006	0.0000	0.0000	0.0000	0.0000
p values	0.0448	0.0632	0.0878	0.0955	0.0325	0.0862	0.0000	0.0000
Beta 2	**0.8909**	**0.9088**	**0.9018**	**0.9524**	**0.8745**	**0.9094**		
Standard Errors	0.0245	0.0304	0.0543	0.0339	0.0067	0.0210		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.3530**	**0.2562**	0.1302	0.0148	**0.8451**	0.5317		
Standard Errors	0.0785	0.0684	0.1589	0.1017	0.4782	0.7611		
p values	0.0000	0.0001	0.2062	0.4422	0.0386	0.2424		
Beta 4			0.5046	**0.2047**				
Standard Errors			0.4175	0.0564				
p values			0.1134	0.0001				
RQ	2.9621	1.7236	2.8851	1.6829	2.9392	1.7264	7.3552	2.1463
Hits in-sample (%)	1.0179	1.0179	1.0179	1.0179	0.9828	1.0179	0.2457	0.7020
Hits out-of-sample (%)	1.3000	1.7000	1.3000	1.9000	1.3000	2.1000	95.5000	18.9000
DQ in-sample								
p values	0.0319	0.3215	0.7902	0.3019	0.5541	0.6251	0.0022*	0.0002*
DQ out-of-sample								
p values	NaN	0.0000	NaN	0.0000	NaN	1.26E-06*	NaN	0*
5% VaR								
Beta 1	**0.0002**	0.0004	**0.0003**	**0.0005**	0.0000	**0.0000**	**-0.0002**	**-0.0001**
Standard Errors	0.0001	0.0007	0.0001	0.0003	0.0000	0.0000	0.0000	0.0000
p values	0.0286	0.2785	0.0325	0.0438	0.1039	0.0331	0.0000	0.0000
Beta 2	**0.9139**	**0.9087**	**0.9289**	**0.9248**	**0.9260**	**0.8962**		
Standard Errors	0.0156	0.0441	0.0190	0.0192	0.0044	0.0070		
p values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Beta 3	**0.1803**	**0.1746**	**0.0684**	-0.0007	0.1921	0.2736		
Standard Errors	0.0325	0.0908	0.0326	0.0461	0.3571	0.2089		
p values	0.0000	0.0272	0.0181	0.4935	0.2953	0.0951		
Beta 4			**0.2100**	**0.2574**				
Standard Errors			0.0418	0.0296				
p values			0.0000	0.0000				
RQ	8.9131	5.8194	8.8207	5.6789	8.9122	5.7833	14.1817	7.0454
Hits in-sample (%)	5.0193	4.9842	4.9842	4.9842	5.0193	5.0544	3.4047	3.7908
Hits out-of-sample (%)	6.2000	4.6000	6.4000	4.8000	7.4000	4.8000	79.5000	42.0000
DQ in-sample								
p values	0.0707	0.0851	0.2487	0.8325	0.0125	0.4831	0*	2.97E-12*
DQ out-of-sample								
p values	NaN	6.14E-07*	NaN	0.00033*	NaN	4.79E-06*	NaN	0*

Note: significant coefficient at 5% formatted in **bold**; "*" denotes rejection from the DQ test at 1% significance level

Figure 21 Summary Table for The Hartford Financial Services Group, INC.VS Allianz, Multi-Line Insurance & Brokerage sector